

# Assimilation of multiple datasets results in large differences in regional to global-scale NEE and GPP budgets simulated by a terrestrial biosphere model



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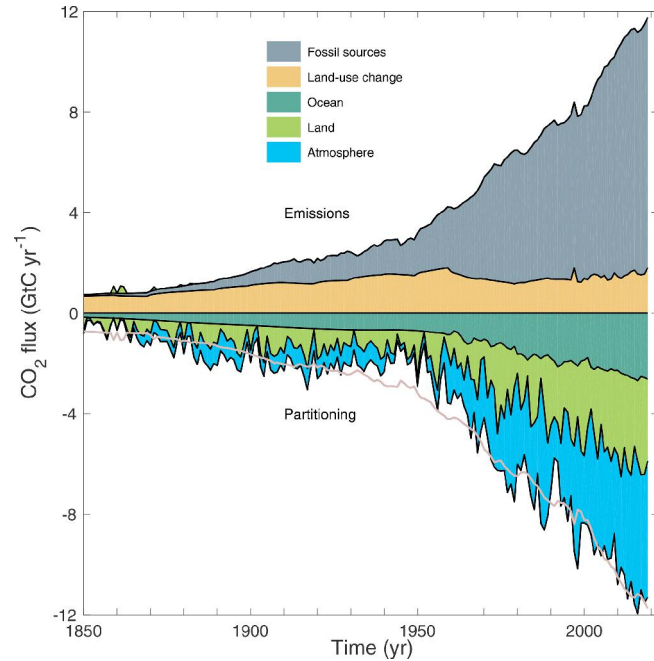
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Gif sur Yvette, France

in Biogeosciences - Discussion  
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# Terrestrial vegetation: the most uncertain component of the Global Carbon Cycle

Quantifying and reducing uncertainty in global C budget projections using Terrestrial Biosphere Models

## The Global Carbon Budget



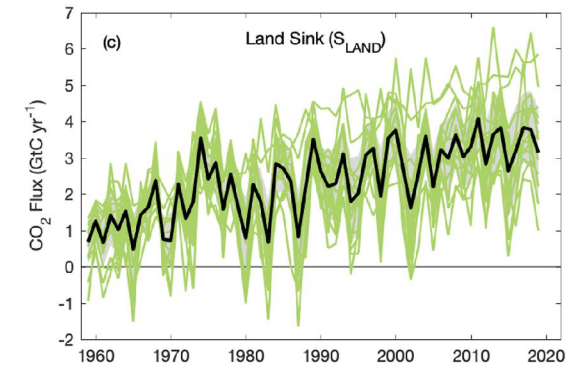
$3.4 \pm 0.9 \text{ GtC.yr}^{-1}$   
over 2010-2020

$$\text{NEE} = \text{GPP} - \text{TER}$$

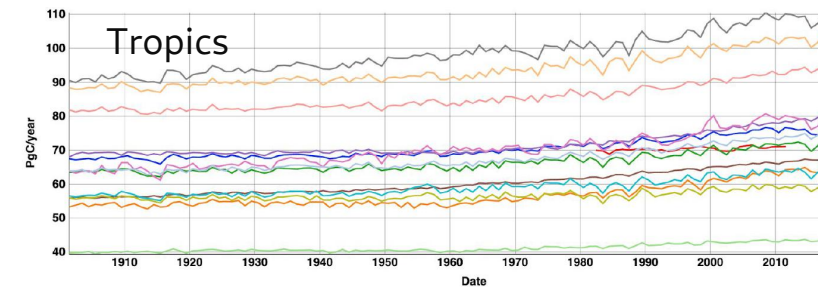
@Friendlingstein et al. (2020)

## Simulations by Terrestrial Biosphere Models

### land C sink - NEE



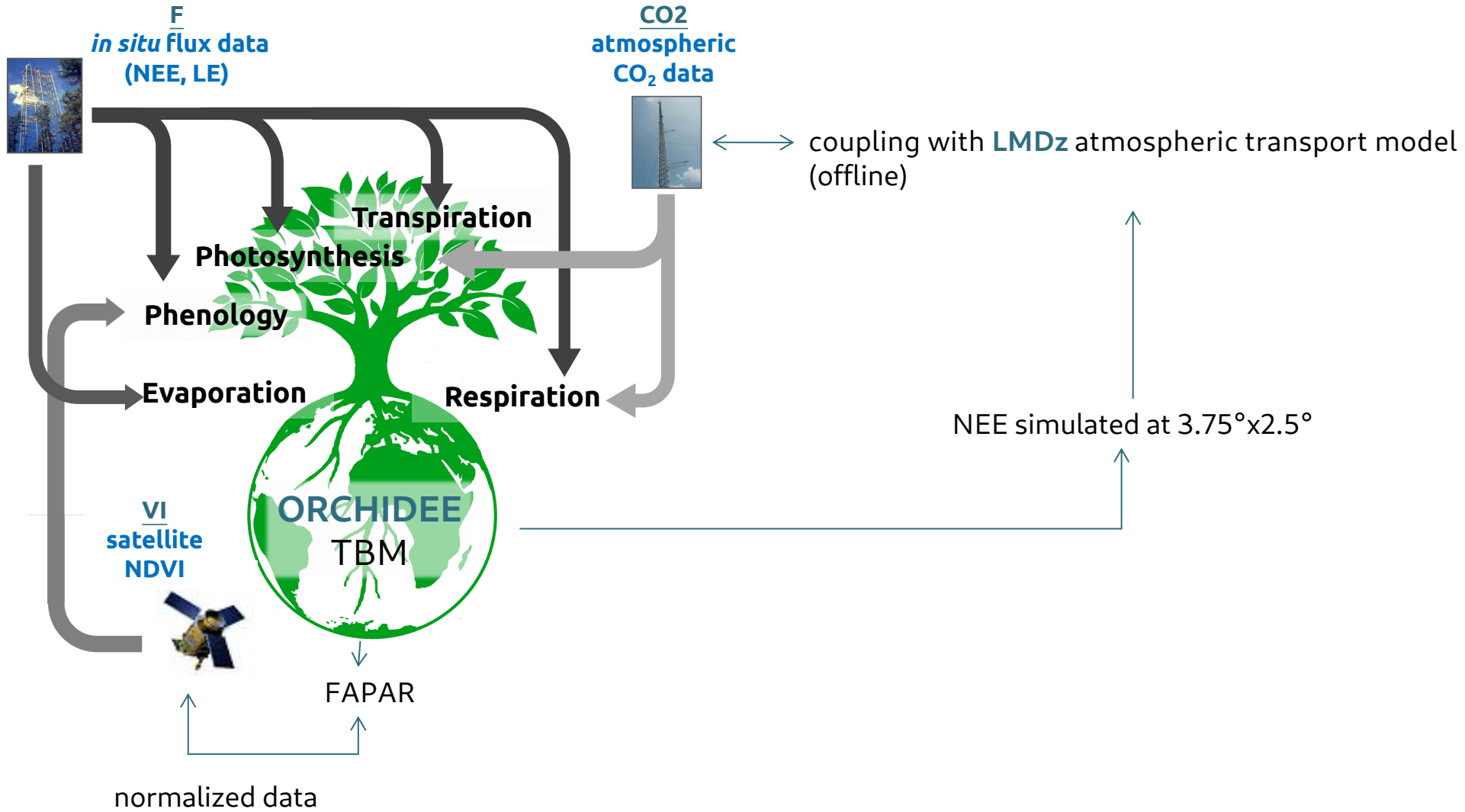
### Gross C flux (GPP)



results from TRENDY V9

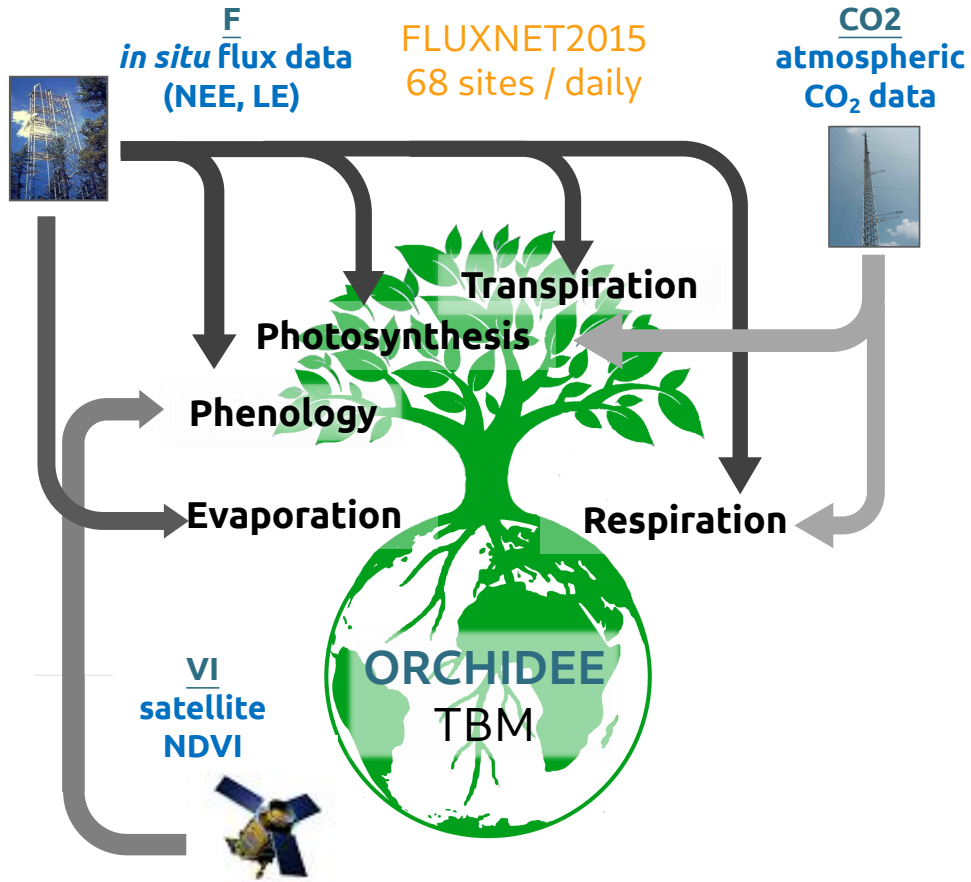
# Model - data fusion to optimize ORCHIDEE parameters

## Datasets



# Model - data fusion to optimize ORCHIDEE parameters

## Datasets



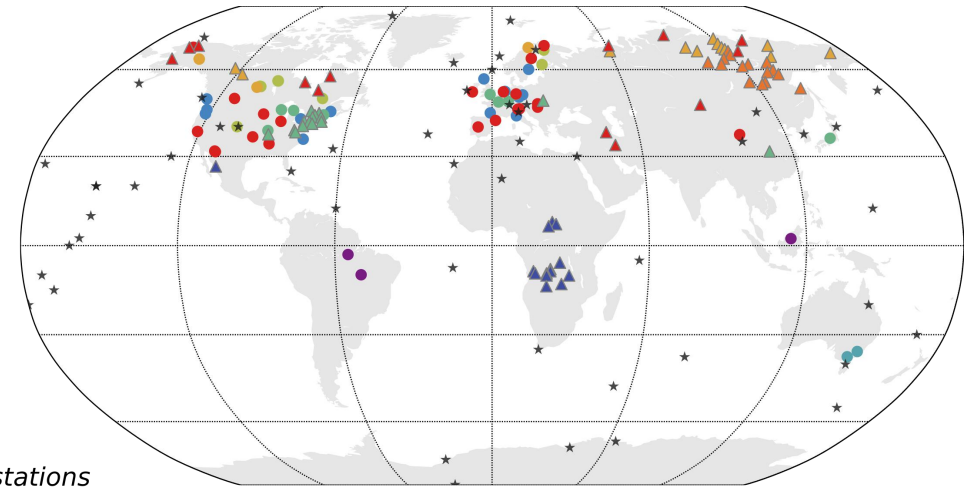
MODIS coll. 5  
15 pixels / PFT  
daily / 0.72°  
2000-2010

53 surface stations  
monthly  
2000-2009

### PFTs

flux	sat
TrEBF	▲
TrDBF	▲
TeENF	▲
TeEBF	▲
TeDBF	▲
BoENF	▲
BoDBF	▲
BoDNF	▲
C3GRA	▲

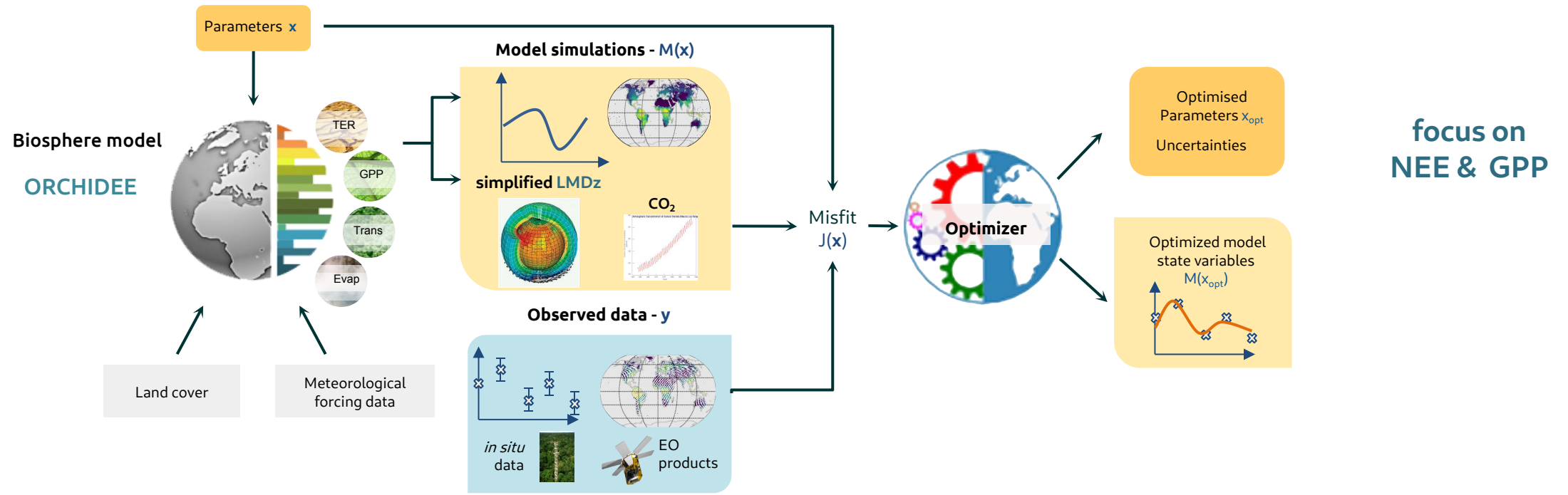
★ atmospheric CO<sub>2</sub> stations



- Not an up-to-date reanalysis of the C cycle!
- Assessment of the useful informational content provided by different data-streams on global C fluxes wrt the set-up and the model structure

# ORCHIDAS assimilation framework

<https://orchidas.lsce.ipsl.fr>



## Misfit function

$$\begin{aligned}
 J(\mathbf{x}) = & \frac{1}{2} \left[ (H_{LMDz} \circ H_{ORCH}(\mathbf{x}) - \mathbf{y}^{CO2})^t \cdot \mathbf{R}_{CO2}^{-1} \cdot (H_{LMDz} \circ H_{ORCH}(\mathbf{x}) - \mathbf{y}^{CO2}) + \right. \\
 & (H_{ORCH}(\mathbf{x}) - \mathbf{y}^F)^t \cdot \mathbf{R}_F^{-1} \cdot (H_{ORCH}(\mathbf{x}) - \mathbf{y}^F) + \\
 & (H_{ORCH}(\mathbf{x}) - \mathbf{y}^{VI})^t \cdot \mathbf{R}_{VI}^{-1} \cdot (H_{ORCH}(\mathbf{x}) - \mathbf{y}^{VI}) + \\
 & \left. (\mathbf{x} - \mathbf{x}^b)^t \cdot \mathbf{B}^{-1} \cdot (\mathbf{x} - \mathbf{x}^b) \right]
 \end{aligned}$$

# Data Assimilation Experiments

Experiment name	Flux data	NDVI data	Atmospheric CO <sub>2</sub> concentrations	Number of optimized parameters	Number of observations
F	x			133	150 792
VI		x		19	149 916
CO2			x	114	6 360
F+VI	x	x		152	300 708
F+CO2	x		x	182	157 152
VI+CO2		x	x	114	156 276
F+VI+CO2 F+VI+CO2-2steps	x	x	x	182	307 068

## Optimized parameters

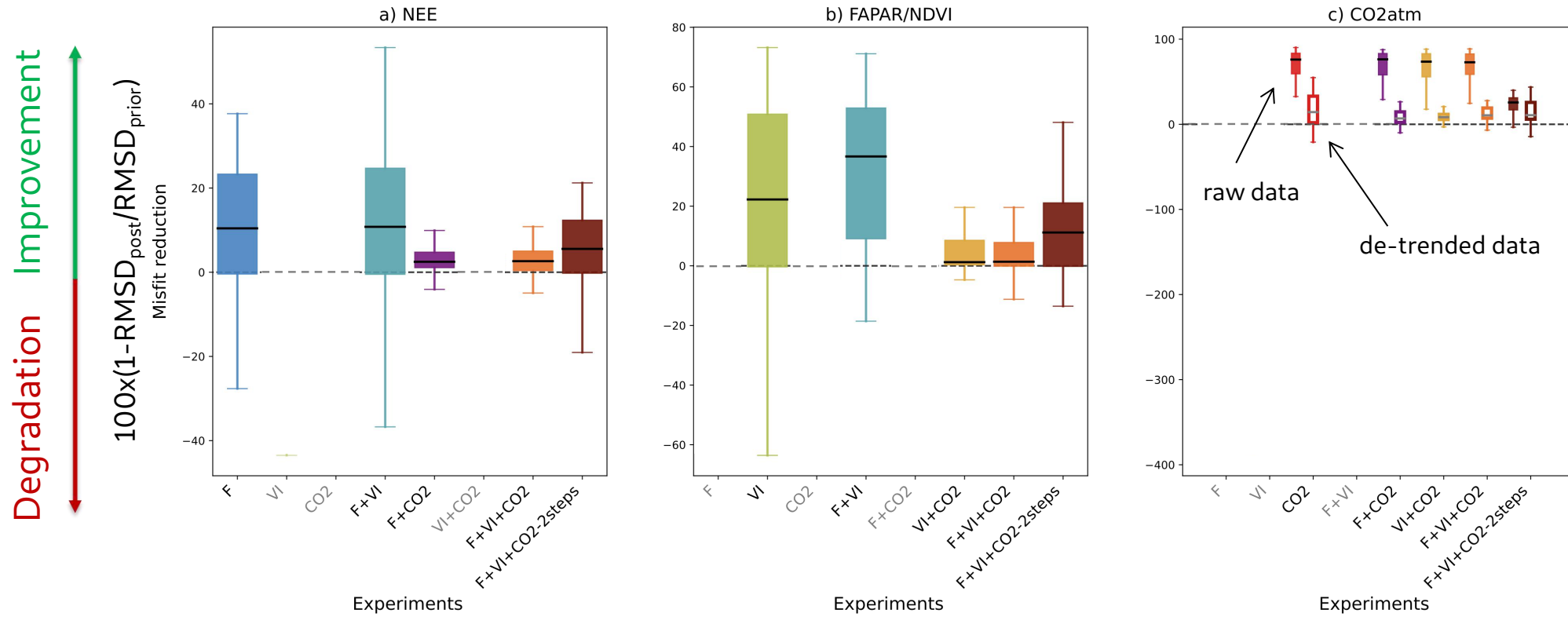
Processes	Parameters	Obs. constraint
Photosynthesis	5 parameters / PFT	F,CO2
Soil Water Availability	1 parameter / PFT	F,CO2
Phenology	5 parameters / PFT	F,VI,CO2
Respiration	3 parameters + $K_{soilC_{site}}$ + $K_{soilC_{reg}}$ (30 regions)	F,CO2 F CO2

## Scientific Questions

- Analyze the compatibility, complementarity, and usefulness, of the different data streams in the frame of a global-scale C data assimilation system
- Assess their potentials to improve the realism of the space-time distribution of **NEE** and **GPP**

# Overall fit to the observations

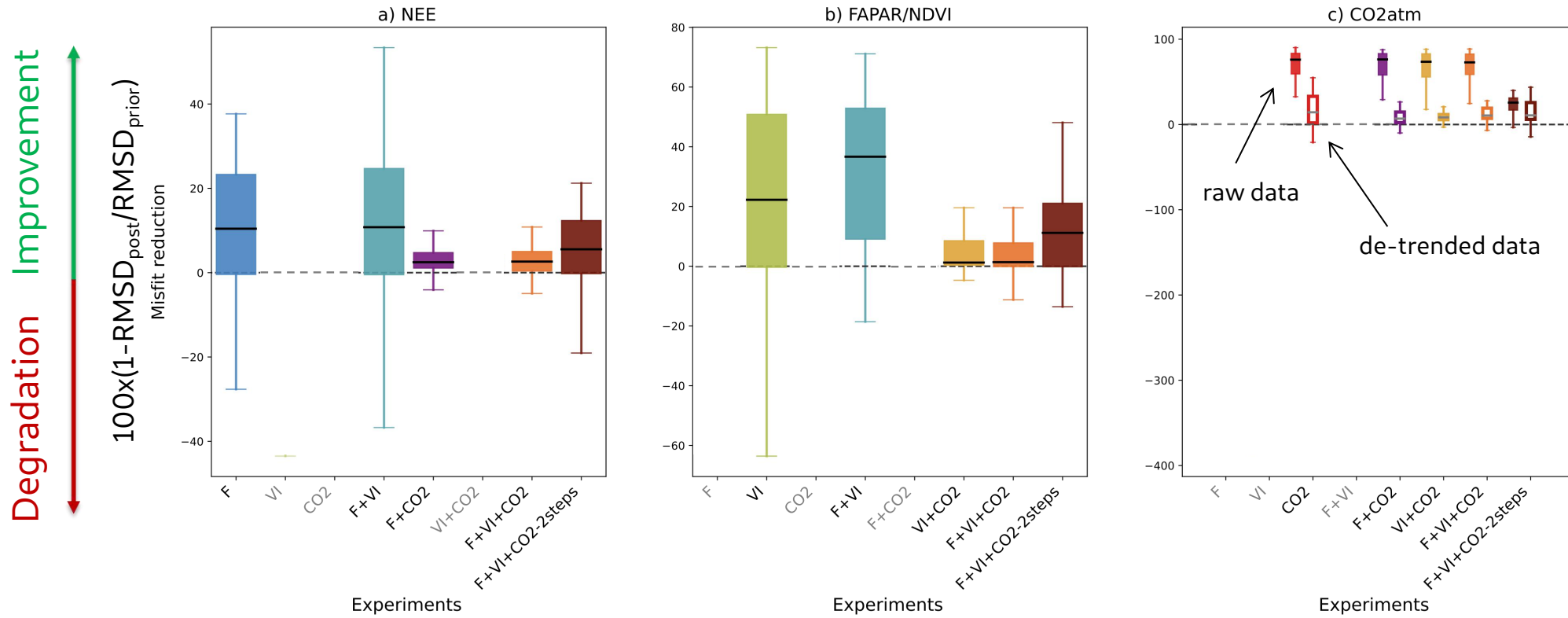
## Reduction of the model-data mismatch wrt the variables assimilated



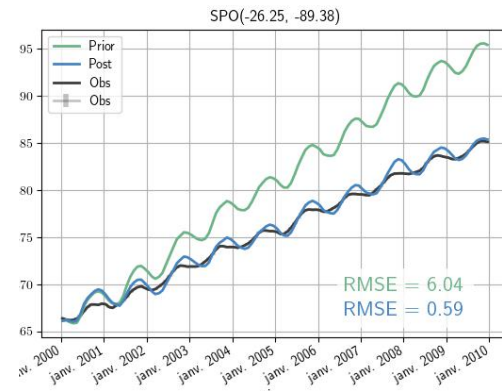
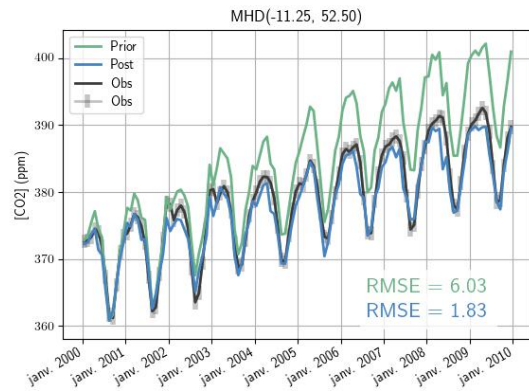
- Model improvement usually better for the experiments where a data stream is assimilated alone
- For the multiple DA with CO2, the 2-step approach lead to the highest improvement wrt F and VI
- For CO2: slight differences wrt raw data, higher variability between experiments wrt de-detrended data

# Overall fit to the observations

## Reduction of the model-data mismatch wrt the variables assimilated



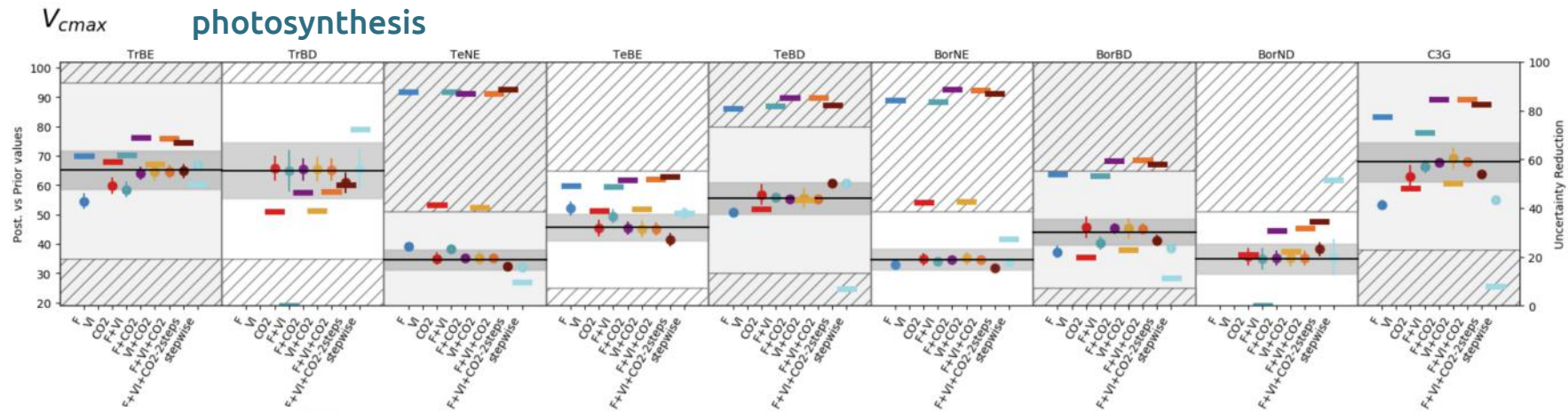
## atmospheric CO<sub>2</sub> time series



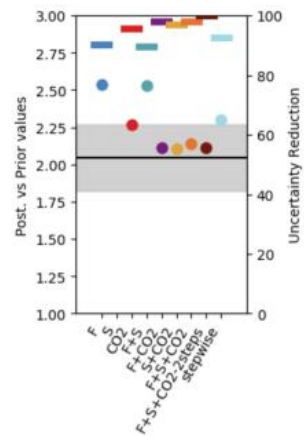
trend correction mostly achieved by the correction of the soil C disequilibrium (multiplicative  $K_{soilC_{reg}}$  parameter)



# Parameter estimates and uncertainties

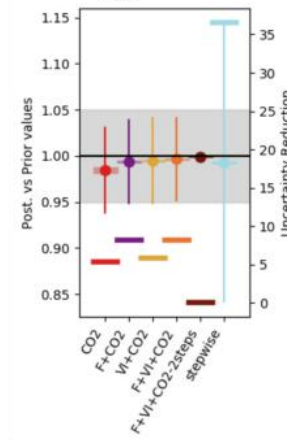


Q10



respiration

$K_{soil}C_{reg}$



- Highest departures from the prior values obtained for single-data stream assimilations
- Correcting the bias in atm. CO2 trend prevails over the improvement of photosynthesis and phenology related parameters
  - higher changes obtained for F and VI, compared to CO2
  - little variability among the 3 data-streams DA w/VI experiments (**but the 2steps one**)

# Relative constraints brought by the different datasets

## Influence matrix

$$\mathbf{S} = \mathbf{R}^{-1}\mathbf{H}^\infty\mathbf{A}\mathbf{H}^\infty\mathbf{t} \quad \text{with} \quad \mathbf{A} = [\mathbf{H}^\infty\mathbf{t}\mathbf{R}^{-1}\mathbf{H}^\infty + \mathbf{B}^{-1}]^{-1}$$

(@Cardinali et al., 2004)

## Global Observation Influence (OI)


> gauges the average influence that each single observation has on the analysis

$$OI = \frac{tr(\mathbf{S})}{m}$$

## Relative Degrees of Freedom for Signal (DFS)

> measures the relative contribution of the data stream  $\sigma$  to the fit

$$DFS = 100 \times \frac{tr(\mathbf{S})}{tr(\mathbf{S}_\sigma)}$$

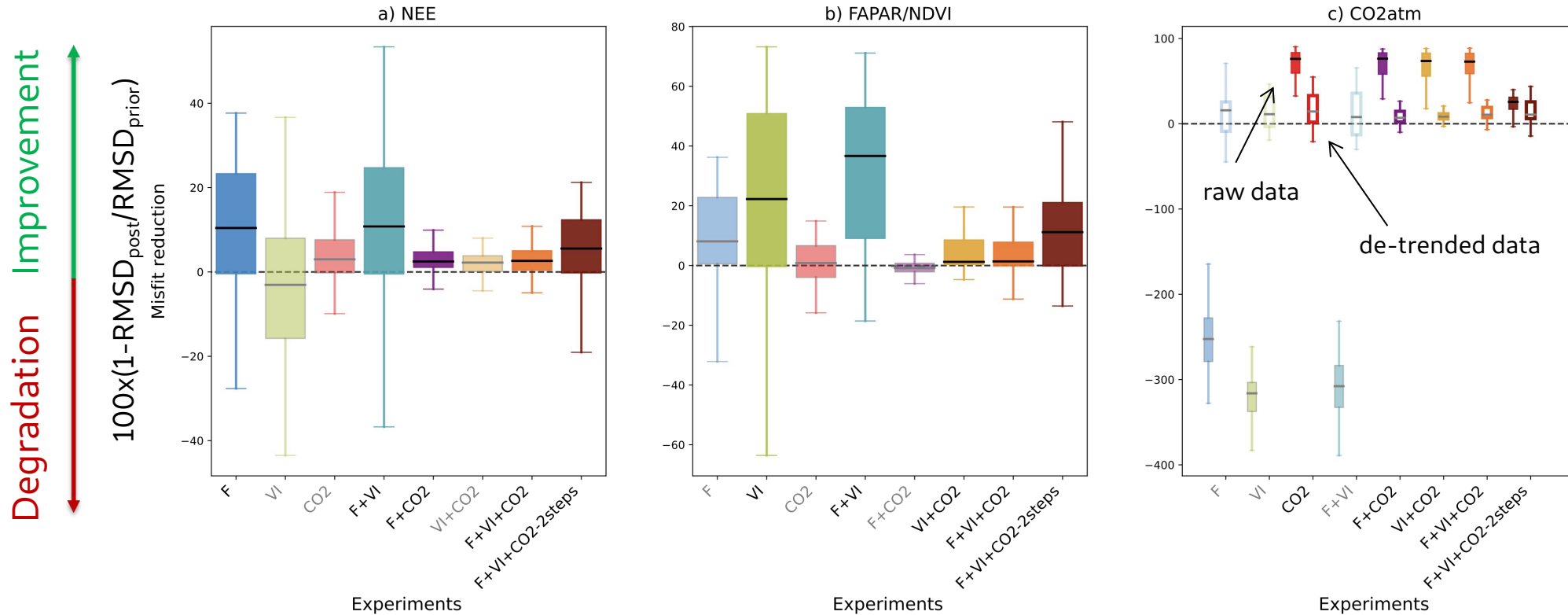
~ x 5 

	OI		DFS	
	1-step	2-step	1-step	2-step
F	0.000586	0.000577	74.65	76.9
VI	0.000048	0.000048	11.12	11.68
CO2	0.002654	0.002035	14.23	11.42

- OI for CO2 is about 5 times higher than that for F with about the same number of optimized parameters BUT about 25 times less observations > impact of the trend correction

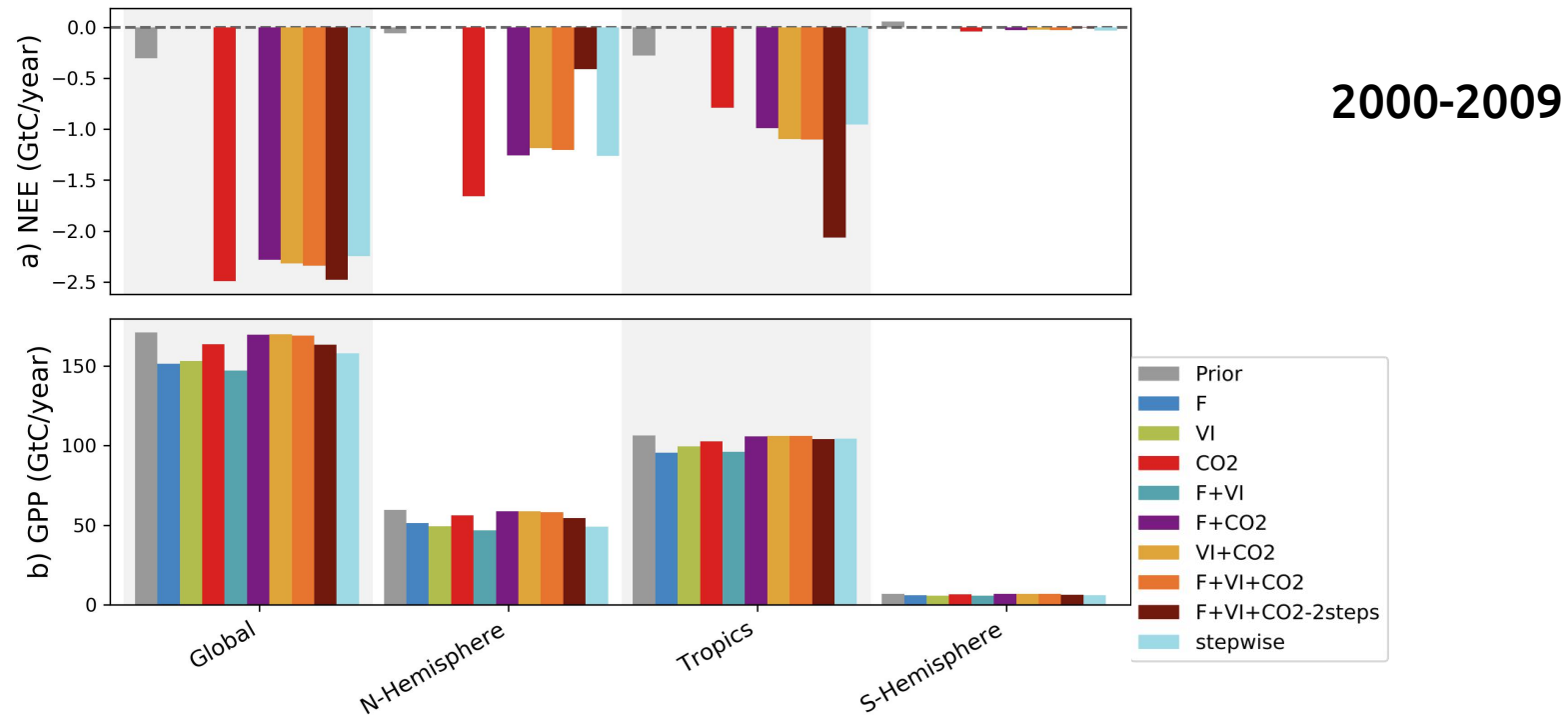
# Overall fit to the observations

## Reduction of the model-data mismatch for all variables



- Simulations using optimized parameters constrained by other data-streams > model degradation can be observed
- The joint assimilation experiments lead to improved model-data agreement and reduce the risk of model degradation (model overfitting wrt a given data-stream)

# Impact of the assimilations on regional to global land C fluxes



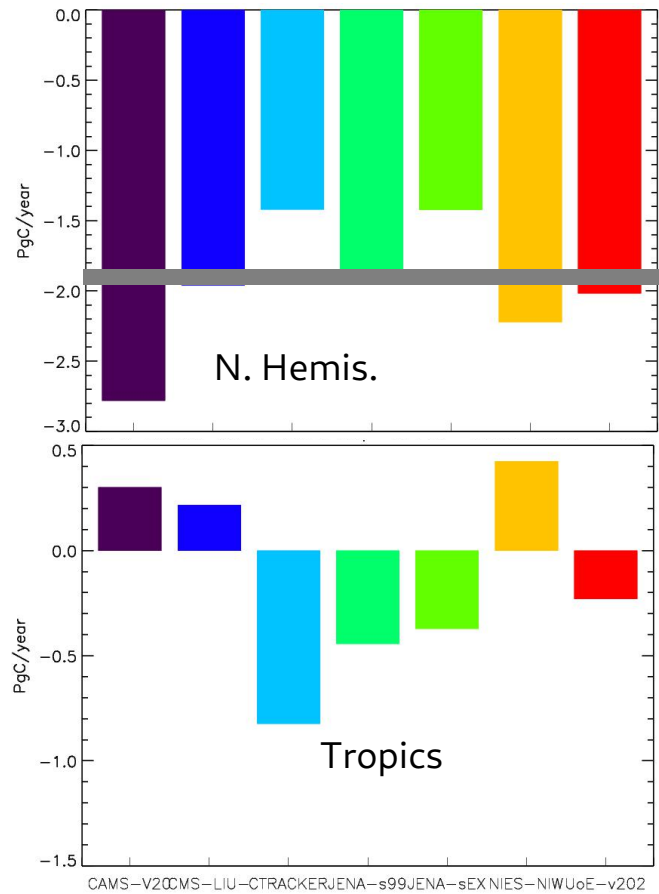
**GCP:** NEE =  $-2.9 \text{ GtC.yr}^{-1} \pm 0.8$

- **F+CO2**, **VI+CO2**, and **F+VI+CO2** : similar NEE and GPP budgets across regions
- **CO2** and **F+VI+CO2-2step** experiments result in distinctly different estimates between N. Hemisphere and Tropics

# Different NH - Tropics partitioning estimated by atmospheric inversions vs TBMs

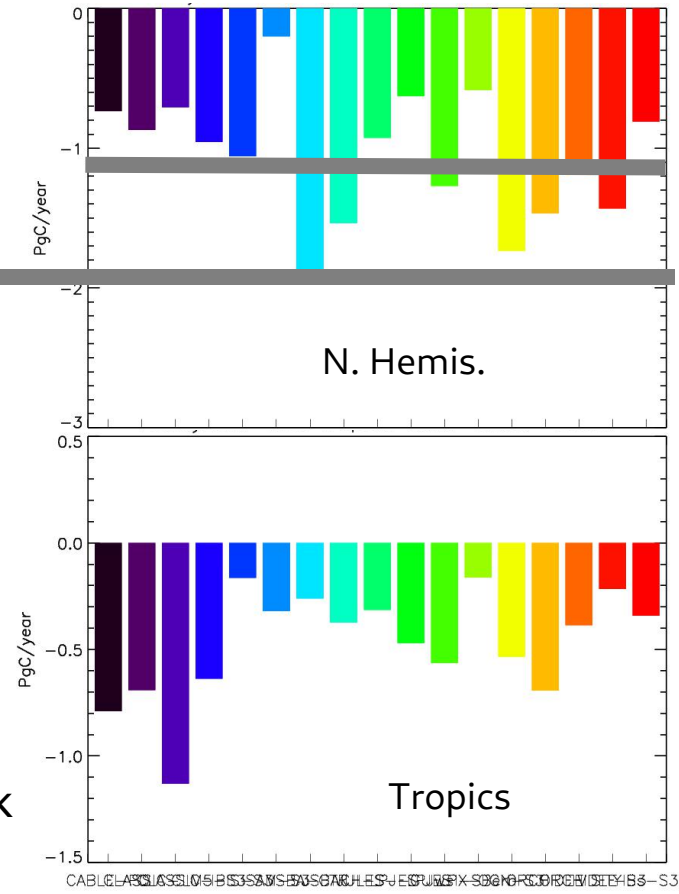
net C fluxes:  
Mean over  
2010-2020

## Atm. inversions (GCP-2021)



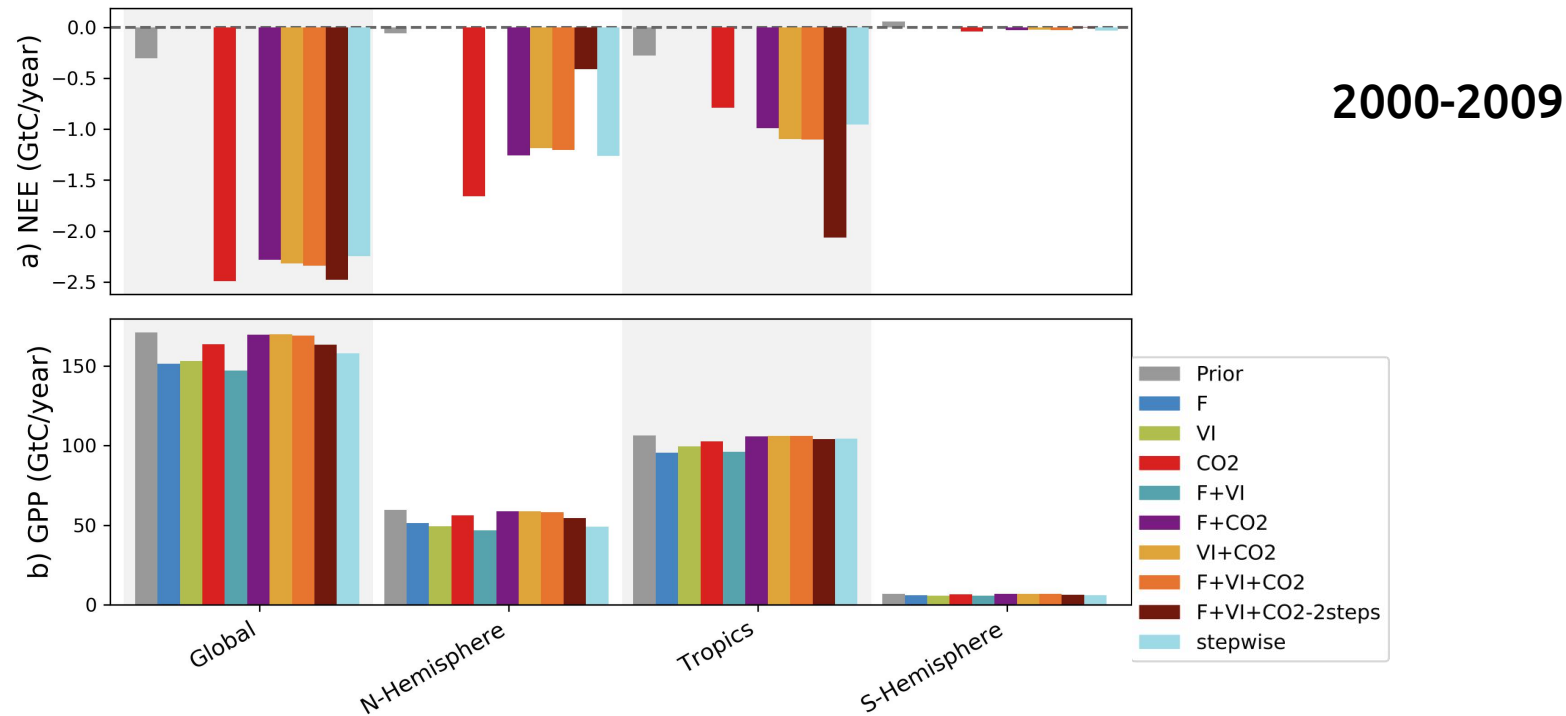
larger sink

## TBMs (TRENDY - V10)



larger sink

# Impact of the assimilations on regional to global land C fluxes



**GCP:** NEE =  $-2.9 \text{ GtC.yr}^{-1} \pm 0.8$

## C budget partitioning between N. Hemisphere and Tropics

- **CO2** > similar regional partitioning as the atmospheric inversions
- **F+VI+CO2-2step** > typical partitioning pattern of TBMs' behavior
- **F+CO2**, **VI+CO2**, and **F+VI+CO2** > approximately equal C sink in the NH and tropics (=> unlike the general pattern for TBMs)

# Take home messages

- Configuration matters
- Atmospheric CO<sub>2</sub> data are crucial for an accurate prediction of the distribution of the terrestrial land sink
  - challenges in handling model-data bias in Bayesian optimisation frameworks
  - sub-optimal optimization of the soil C disequilibrium with our approach based on a model spin-up without a long transient run (not TRENDY like)
  - 2step approach: illustrate how the informational content of the data-streams relative to C fluxes is enhanced once soil C disequilibrium is modeled in a more “realistic” way
- Diagnostics for system evaluation
  - relative informational content brought by each data stream
  - consistency of the error statistics on parameters and observations (Desrozier et al. (2005))
  - optimisation efficiency
- Assimilating simultaneously multiple datasets is preferable to optimize the values of the model parameters and avoid model overfitting